# Speech recognition and synthesis

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# Introduction

Classical
TTS: Text ⇒ Accents ⇒ Phonemes ⇒ Prosody ⇒ Sound
ASR: Sound ⇒ MFCC ⇒ HMM ⇒ Language Model ⇒ Text

### TTS and ASR: Recognition by synthesis, or synthesize by recognition

- Both synthesis and recognition work by comparing speech to a stored model
- Recognition works by synthesizing speech
- Synthesis works by reproducing stored speech
- Can a synthesizer really be used to recognize?
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# Introduction: The computational challenge

## There is no data like more data, but how to use it?

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- Speech corpora become exponentially larger over time
- Current HMM speech recognition only marginally better than 10 years ago
- Current synthesis idem
- How can computer speed and corpus size be harnessed?

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- Eg, piecewise polynomials, linear dynamic systems, nonlinear dynamic systems
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## HMM derives abstract model from examples

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## Store as much speech as possible

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- What was said, by whom, and how
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   The result is a segmentation file with phoneme transcriptions and phonetic boundary timings
2. Merge consecutive segments at will to produce supra-phonemic templates
3. Determine meta-information for each segment
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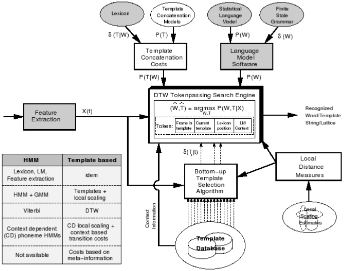

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| Lexicon, LM, Feature extraction | idem |
| HMM + GMM | Templates + local scaling |
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## Correspondense between HMM and Template based ASR

- Distances are calculated to template cluster centroids
- Clustered acoustic vectors are a kind of degenerated HMM
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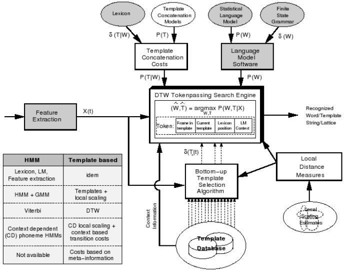

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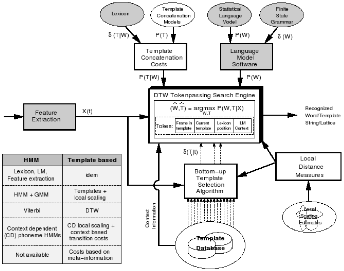

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## There is never enough speech

- Every utterance and situation are different
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- . . . and it is never enough

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## Add a lot of flexibility

- HMM states can average over a cluster of contexts
- Store the dynamics of spectral change etc.
- HMM models for a new speaker can be learned
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- The difference can be determined on just a little speech
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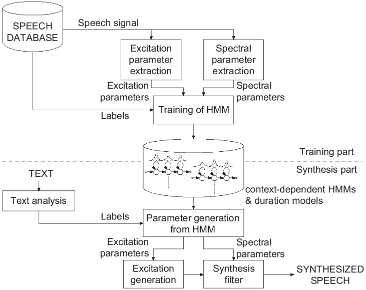
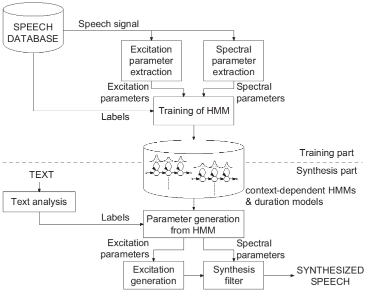


## Store abstract, generalized units

- HMM states summarize spectrum words
- Model intonation (excitation) separately
- Label HMMs with contextual information

[Tokuda et al.(2002)Tokuda, Zen, and Black]

# HMM based TTS



## Store abstract, generalized units

- HMM states summarize spectrum words
- Model intonation (excitation) separately
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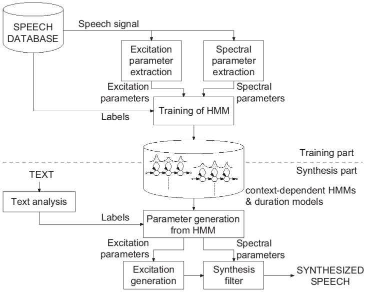
[Tokuda et al.(2002)Tokuda, Zen, and Black]

# HMM based TTS



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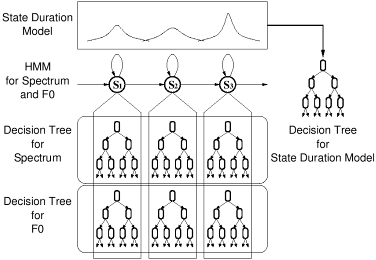

## Decision-tree based context clustering

- Many contextual factors (e.g., phone identity factors, stress-related factors, locational factors)
- Context-dependent HMMs
- Not enough speech and time ⇒ Cluster

[Tokuda et al.(2002)Tokuda, Zen, and Black]

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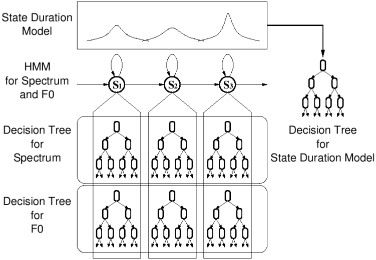

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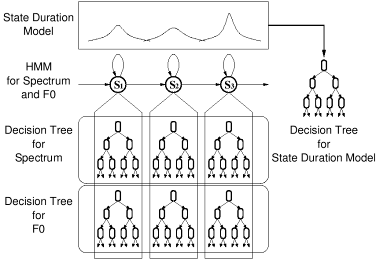

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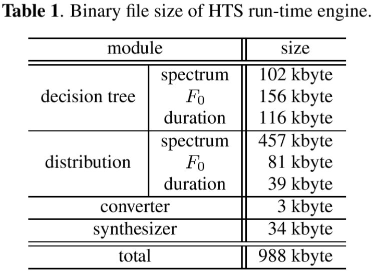

**Table 1**. Binary file size of HTS run-time engine.

| module | | size |
|---|---|---|
| decision tree | spectrum | 102 kbyte |
| | $F_0$ | 156 kbyte |
| | duration | 116 kbyte |
| distribution | spectrum | 457 kbyte |
| | $F_0$ | 81 kbyte |
| | duration | 39 kbyte |
| converter | | 3 kbyte |
| synthesizer | | 34 kbyte |
| total | | 988 kbyte |

## Reduce footprint

- Small enough for PDAs
- Ten times Real-Time (on P4)
- HTS example using Alan's voice

[Tokuda et al.(2002)Tokuda, Zen, and Black]

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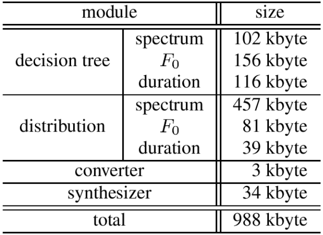

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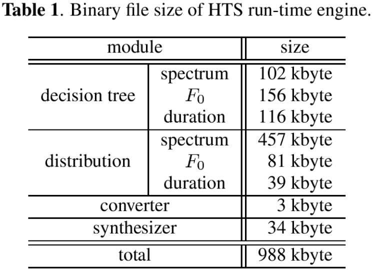

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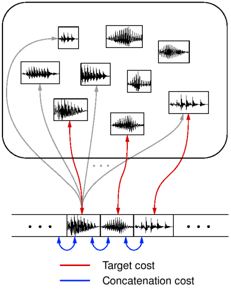

## Classical Unit Selection scheme

- Concatenate using Target and Concatenation costs
- Use whole speech database
- Concatenate in real time

[Tokuda et al.(2002)Tokuda, Zen, and Black]

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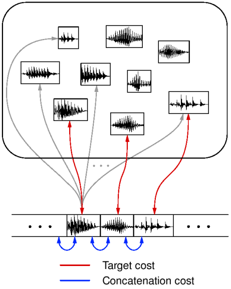

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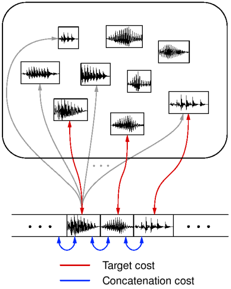

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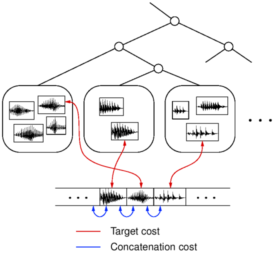

## HTS scheme

- Cluster all units on context in advance
- But use only statistics of cluster, not original templates
- Concatenation cost corresponds to dynamic feature parameter

[Tokuda et al.(2002)Tokuda, Zen, and Black]

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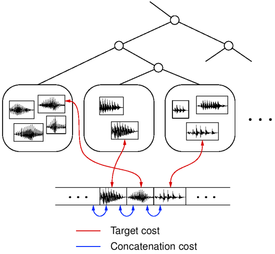

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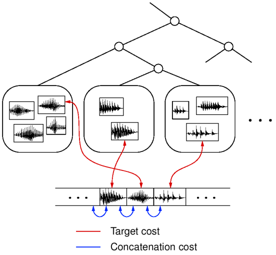

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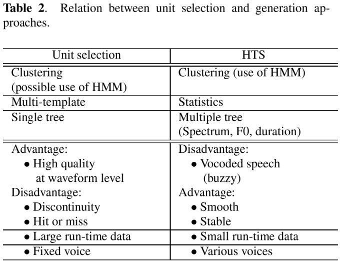

**Table 2**. Relation between unit selection and generation approaches.

| Unit selection | HTS |
|---|---|
| Clustering<br>(possible use of HMM) | Clustering (use of HMM) |
| Multi-template | Statistics |
| Single tree | Multiple tree<br>(Spectrum, F0, duration) |
| Advantage:<br>• High quality at waveform level<br>Disadvantage:<br>• Discontinuity<br>• Hit or miss | Disadvantage:<br>• Vocoded speech (buzzy)<br>Advantage:<br>• Smooth<br>• Stable |
| • Large run-time data | • Small run-time data |
| • Fixed voice | • Various voices |

## Comparison

- Unit selection often very good, sometimes really bad
- HMM often bad (vocoder)
- HMM is much smaller and adaptable (retraining)

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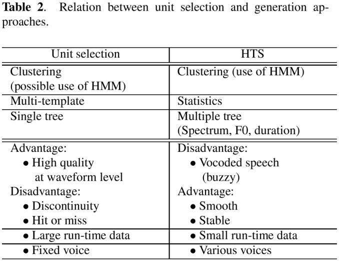

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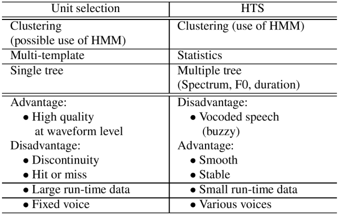

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# Further Reading I

James F. Allen, Donna K. Byron, Myroslava Dzikovska, George Ferguson, Lucian Galescu, and Amanda Stent.
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Helmer Strik, Albert Russel, Henk van den Heuvel, Catia Cucchiarini, and Lou Boves.
A spoken dialog system for the dutch public transport information service.
*Int. Journal of Speech Technology*, 2:121–131, 1997.
URL http://lands.let.ru.nl/literature/strik.1996.4.ps.
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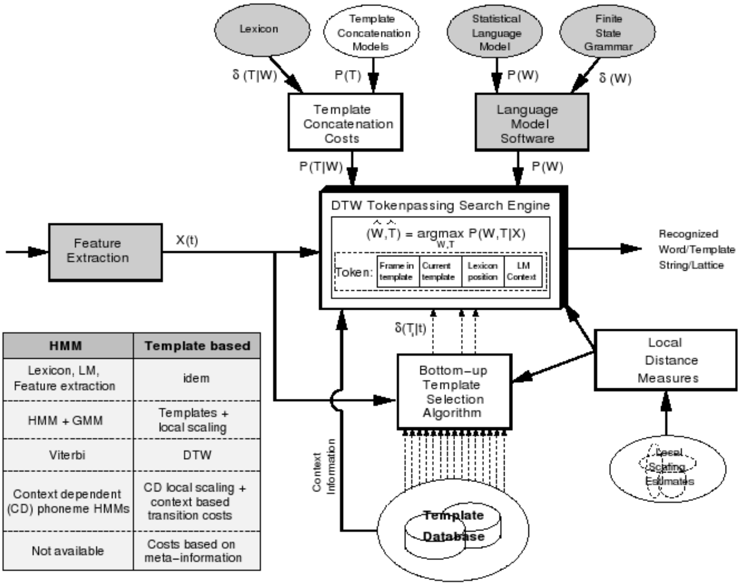
# Further Reading II

W. Wesseling and R. J. J. H. van Son.
Timing of experimentally elicited minimal responses as quantitative evidence for the use of intonation in projecting TRPs.
In *Proceedings of Interspeech2005*, Lisbon, 2005.

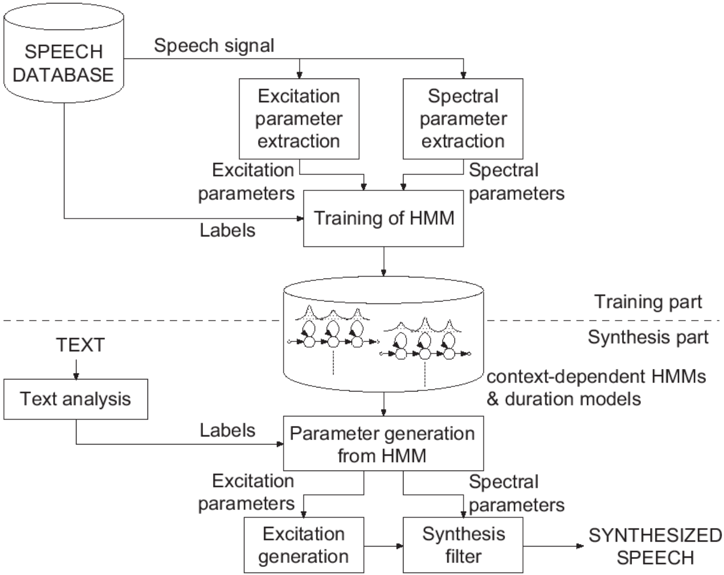
Wieneke Wesseling and R.J.J.H. Van Son.
Early Preparation of Experimentally Elicited Minimal Responses.
In *Proceedings of SIGdial 2005*, September 2005.
URL `http://www.fon.hum.uva.nl/rob/Publications/ArtikelSIGdial2005.pdf`.

# Architectural overview template based ASR



| HMM | Template based |
|---|---|
| Lexicon, LM, Feature extraction | idem |
| HMM + GMM | Templates + local scaling |
| Viterbi | DTW |
| Context dependent (CD) phoneme HMMs | CD local scaling + context based transition costs |
| Not available | Costs based on meta−information |

# Architectural overview HMM based synthesis



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Also add information on how to contact you by electronic and paper mail.

If the program is interactive, make it output a short notice like this when it starts in an interactive mode:

> *Gnomovision version 69, Copyright (C) yyyy name of author*
> *Gnomovision comes with ABSOLUTELY NO WARRANTY; for details type ‘show w’.*
> *This is free software, and you are welcome to redistribute it under certain conditions; type ‘show c’ for details.*

# The GNU General Public License IX

The hypothetical commands `show w` and `show c` should show the appropriate parts of the General Public License. Of course, the commands you use may be called something other than `show w` and `show c`; they could even be mouse-clicks or menu items—whatever suits your program.
You should also get your employer (if you work as a programmer) or your school, if any, to sign a “copyright disclaimer” for the program, if necessary. Here is a sample; alter the names:

> *Yoyodyne, Inc., hereby disclaims all copyright interest in the program*
> *‘Gnomovision’ (which makes passes at compilers) written by James Hacker.*
> *signature of Ty Coon, 1 April 1989*
> *Ty Coon, President of Vice*

This General Public License does not permit incorporating your program into proprietary programs. If your program is a subroutine library, you may consider it more useful to permit linking proprietary applications with the library. If this is what you want to do, use the GNU Library General Public License instead of this License.